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Authors
Ferrer, Emilio
Rast, Philippe

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Partitioning the Variability of Daily Emotion Dynamics in Dyadic Interactions with a Mixed-Effects Location Scale Model

Emilio Ferrer, **Philippe Rast**

University of California, Davis

Abstract

We examine the daily exchanges in affect and emotional experiences of individuals in dyads using a mixed-effects location scale model. We argue that this method is useful to characterize the daily fluctuations in emotions for each individual as well as their interrelations over time. Furthermore, we illustrate how to consider the potential effect of factors external to the dyads' emotion dynamics, an aspect often ignored in emotion research. In particular, we show how daily weather may influence within-person variability of affect toward one's relationship, beyond the influence of one's and the partner's affect. We interpret our findings in the context of emotion research and methodology for dyadic interactions.

Dyadic interactions change over time and involve time-lagged sequences. To examine such dynamics, two features are necessary: (a) an intense set of measurements that reflects the dyad's fluctuations over time and the time dependency of those fluctuations, and (b) models that can accurately and reliably capture such kinetics. One design suited to identify these features is the intra-individual variability design. In this design, a person is measured at multiple occasions and multiple variables, allowing researchers to study processes, as they unfold over time.

A number of modeling techniques are available that use the intensive measurements of the intra-individual variability design. One of such techniques is dynamic factor analysis (DFA; Browne & Nesselroade, 2005; Molenaar, 1985). DFA combines factor analysis with time series, and allows the identification of the factorial structure of the data as well as its time-related signature (Browne & Nesselroade, 2005; Ferrer & Zhang, 2009). DFA has been used to examine the ups and downs of daily emotions in couples (Ferrer & Nesselroade, 2003; Ferrer & Widaman, 2008). DFA is particularly useful to address questions related to emotion dynamics, such as the number and nature of factors underlying affect (e.g., positive and negative affect) together with possible influences between the individuals' emotions over time (e.g., from one person to the other across days).

Increasingly popular in the social and behavioral sciences are differential equation models (DEM). DEM are useful for modeling data that are continuous, such as time series of physiological signals or fMRI. In dyadic interactions, DEM have been used as heuristics to develop theoretical models (Felmlee, 2006; Felmlee & Greenberg, 1999). In addition, they

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Correspondence to: Emilio Ferrer, Department of Psychology, University of California, Davis, eferrer@ucdavis.edu.

have been implemented to model empirical data on the emotional interaction between spouses and subsequent break-up (Gottman, Murray, Swanson, Tyson, & Swanson, 2002), daily intimacy and disclosure in married couples (Boker & Laurenceau, 2006), and the dynamics of emotional experiences between individuals in close relationships (Chow, Ferrer, & Nesselroade, 2007; Chow et al., in press; Ferrer & Helm, 2013; Ferrer & Steele, 2012, 2014; Ferrer, Steele, & Hsieh, 2012; Steele, Ferrer, & Nesselroade, 2014).

Arguably the most popular technique for analyzing data of dyadic interactions is multilevel modeling (MLM). MLM takes into account clustering in the data (e.g., repeated observations within individuals, individuals within couples) and partitions the variance accordingly. In research with dyads, MLM has been used to distinguish among actor, partner, and interaction effects (Campbell & Kashy, 2002; Kenny, Kashy, & Cook, 2006), investigate the quality of marital roles in married couples (Raudenbush, Brennan, & Barnett, 1995), characterize the interrelations of affect between romantic partners (Butner, Diamond, & Hicks, 2007), model daily intimacy and disclosure in married couples (Bolger & Laurenceau , 2013; Laurenceau, Troy, & Carver, 2005), and to capture emotional contagion between couple members undergoing a stressful event (Thomson & Bolger, 1999).

MLM is a framework particularly useful to consider hierarchical structure in the data and to incorporate potential influences from covariates (both time-varying and invariant). Some of its limitations include the difficulty to capture the factorial structure in multivariate data, quantify temporal dynamics, handle small samples - or single-case studies -, or identify unique idiosyncrasy across the units in the data (Ferrer et al., 2012; Walls & Schafer, 2006).

In addition to the drawbacks specific to each approach, one limitation shared by all these modeling frameworks is the lack of information about the residuals. Generally speaking, residuals represent the part that is unexplained by the model. In most approaches, such residuals (e.g., random shocks, innovations) represent external influences that are not being considered by the model and that are not part of the data. MLM can accommodate various residual structures, but it is often hard to invoke a theory that dictates these residuals. Moreover, a general criticism of most models for dyadic interactions is that they represent closed systems, without information about external sources that that may permeate the dyad over time.

One relatively recent technique suited to overcome this criticism about residuals is the mixed-effects location scale model (LSM; Cleveland, Denby, & Liu, 2002; Hedeker, Mermelstein, & Demirtas, 2008; Hedeker, Mermelstein, Berbaum, & Campbell, 2009; Rast, Hofer, & Spark, 2012; see also Cleasby et al., 2015). LSM allows partitioning the residuals in systematic ways. In particular, this modeling approach is useful to separate within- and between-subjects variability (Rush & Hofer, 2014), and to characterize the mean structure and variability of the response, allowing explanatory variables to account for such variation.

In social science research, LSM has been used in only a handful of occasions. For example, it was used to examine dispersion in school achievement as a function of socioeconomic status (Leckie et al., 2014), or to examine variability in adolescents' mood following a smoking event (Hedeker et al., 2008). More recently, LSM was used to model the fluctuations in individuals' affect during one week (Rast et al., 2012). In that study, individual differences in within-person variability of negative and positive affect were accounted for by perceived stress. With regard to dyadic interactions, to the best of our knowledge, LSM has yet to be used. Here, we briefly describe this modeling approach (see Rast & Ferrer, 2017, for full details) and illustrate its implementation using affect data from dyads.

Assume a response variable *Y*, measured on individual *i* at occasion j. A standard linear mixed-effect model can be written as

$$\mathbf{y}_{\mathrm{i}} = \mathbf{X'}_{\mathrm{i}}\beta + \mathbf{Z'}_{\mathrm{i}}\mathbf{b}_{\mathrm{i}} + \boldsymbol{\varepsilon}_{\mathrm{i}}\ , \tag{1}$$

where $\mathbf{y_i}$ is the response vector containing observations for individual *i*. $\mathbf{X_i}$ is the design matrix for the fixed effects, β represents the fixed effects parameters, $\mathbf{Z_i}$ is the matrix of random effects, $\mathbf{b_i}$ is the vector with the random effects coefficients, and $\boldsymbol{\varepsilon}_{\mathrm{i}}$ denotes the residuals. In a standard linear mixed-effect model, the random effects are commonly assumed to follow a normal distribution with **0** mean and **Φ** covariance matrix of random effects, including variances σ^2_b and covariances $\sigma_{bb'}$. Similarly, the residuals $\boldsymbol{\varepsilon}_{\mathrm{i}}$ are assumed to be normally distributed with mean **0** and covariance of $\sigma^2_{\boldsymbol{\varepsilon}}\boldsymbol{\Psi}_i$.

Typically, a standard linear mixed-effect model assumes that the within-person variance $\sigma^2_{\boldsymbol{\varepsilon}}$ is fixed. In LSM, however, this restriction is relaxed and $\sigma^2_{\boldsymbol{\varepsilon}ij}$ is allowed to vary at the individual level and across time. The residual variance is now a function of a set of explanatory variables such as

$$\sigma^2_{\varepsilon ij} = \exp\left(\mathbf{W'}_{ij}\boldsymbol{\tau} + \mathbf{V'}_{ij}\mathbf{t}_i\right), \tag{2}$$

where $\mathbf{W}_{ij}$ and $\mathbf{V}_{ij}$ denote time varying covariates (for the fixed and random effects) that affect the within-person variance, $\boldsymbol{\tau}$ is a vector of regression coefficients, and $\mathbf{t}_i$ represents random effects, which are assumed to be normally distributed with mean 0 and variance σ^2_t. Because of the time-varying influences, the within-person variance $\sigma^2\boldsymbol{\varepsilon}\cdot$ is allowed to vary both across individuals and across time. Finally, the exponential function is used to ensure the variance is positive (see Hedeker et al., 2008, 2009; Rast et al., 2012).

This LSM specification can be extended to the dyad level by including an additional nested level *k*, as

$$\mathbf{y}_{\mathrm{ik}} = \sum_{k=1}^{m} d_k\left(\mathbf{X'}_{\mathrm{ik}}\beta + \mathbf{Z'}_{\mathrm{ik}}\mathbf{b}_{\mathrm{ik}} + \ \varepsilon_{\mathrm{ik}}\ \right), \tag{3}$$

where $k = 1, \ldots, m$, represents the number of units in the level (two in our case). Here we define *m=2* dummy variables, one for each partner in the dyad, where $d_k = 1$ if a given measure is y_k and $d_k = 0$ otherwise.[1] The elements in d_k are then mutually exclusive and

[1]This is a general expression but the specific coding scheme may vary depending on the statistical program. For example, in SAS PROC NlMixed, only one dummy variable (0,1) is necessary.

ensure that the model is estimated either for one partner or the other partner in the dyad. The remaining components of the model are extended in a similar way.

Most of the LSMs have been estimated using Bayesian procedures (e.g., MCMC; Rast et al., 2012), or a combination of maximum likelihood for the fixed effects and empirical Bayes methods for the random effects (Hedeker & Nordgren, 2013). Here, we use maximum likelihood with dual quasi-Newton optimization, as implemented in SAS PROC NLMixed (SAS, 2014), a flexible program that allows constraints such as ensuring predicted values remain in bounds.[2]

Empirical Example

We use data from 165 heterosexual couples recruited as part of a study of dyadic interactions (Ferrer et al., 2012; Ferrer & Widaman, 2008). Participants include couples involved in a romantic relationship who completed a daily questionnaire about their affect for up to 90 consecutive days. They ranged in age from 17 to 74 years ($M = 25{:}08$, $SD = 10{:}39$) and reported having been in the relationship from 1 month to 54 years ($M = 3{:}39$, $SD = 6{:}52$).

The main measure in our analyses is *Relationship-Specific Affect* (RSA; Ferrer et al., 2012), a set of 18 items (ranging from 1 to 5) tapping into positive and negative emotional experiences specific to one's relationship. In addition to positive and negative affect subscales, we created a ratio of affect *[positive / (positive + negative)]* (Schwartz et al., 2002). Research has shown that different ratios can describe various states of affect, ranging from psychopathological, normal, and optimal states. In particular, ratios of about .70 to .80 have been found to indicate normal and optimal functioning in individuals (Schwartz et al., 2002) and couples (Gottman, 1994). Finally, we use maximum daily temperature as an indicator of the day's weather (Ferrer, Gonzales, & Steele, 2013).

Results

The specific model fitted to the data (positive affect or affect ratio) was the following:

$$Y_{ijk} = \sum_{k=1}^{m} d_k \left(\beta_{0ik} + \beta_{1ik} \cdot \text{self}_{j-1} + \beta_{2ik} \cdot \text{partner}_j + e_{ijk} \right) \quad (4)$$

and

$$\sigma^2_{\varepsilon ijk} = \exp\left(\boldsymbol{\tau}_{\mathbf{0}ik} + \boldsymbol{\tau}_{1ik} \cdot \max_{ijk} \right), \quad (5)$$

where affect on any given day j is a function of an intercept (β_0), one's affect the previous day j-1 (β_1), and the partner's affect on the same day j ($\beta 2$).[3] The within-person variance $\sigma^2_{\varepsilon ijk}$ is a function of an intercept (τ_0) and an effect due to the maximum daily temperature (τ_1).

[2]Input code from SAS proc NLMixed is available from the authors via email.
[3]We decided to include partner effects from the same occasion because participants were asked to fill out the questionnaires at the end of the day, reflecting on the relationship throughout the day. It is reasonable to presume that both individuals completed the questionnaire thinking about their partner and, thus, affect for one person might be influenced by his or partner that same day.

Table 1 and 2 contain results from the LSM fitted to the dyadic data (for the affect ration and positive affect, respectively). For example, the results from Table 1 indicate that, on any given day, the affect ratio for each dyad member was a function of: an intercept (β_0 = .243 and .292, for females and males, respectively), their own affect the previous day ($\beta_{1t\text{-}1}$ = .259 and .265), and their partner's affect on the same day (β_{2t} = .359 and .329). These estimates represent population-level effects that vary across individuals in both the intercept (σ^2_0 = .033 and .011, for females and males, respectively), the auto-regression (σ^2_1 = .036 and .028), and the partner effects (σ^2_2 = .080 and .065).

With regard to the scale part that governs the within-person variance of the model, such within-person variance is a function of an intercept (τ0 = −5.05 and −4.93), representing the average variance on the log-scale, and an effect due to the daily temperature (τ_1 = −.003 and −.007), denoting a decrease in the within-person variance on days with higher temperature. These fixed-effects for the scale also have random components, indicating variation across individuals in the intercept ($\sigma^2_{\tau 0}$ = 25.07 and 15.16) and the weather-related slope ($\sigma^2_{\tau 1}$ = .052 and .065) of the within-person variance. Given the exponential form of Equation 5, and the average maximum temperature in our data (*M* = 64.84 degrees), the within-person variance can be rescaled into the original metric of the variable ($\sigma^2_{\varepsilon ij}$ = .0054 and .0045, for females and males, respectively).

When this LSM model was compared to a standard mixed-effects dyadic model without scale components, the fit decreased substantially ($\chi^2(10) = 43$). This provides support for the parameters partitioning the within-person variation. The parameter estimates in Table 2 can be interpreted in a similar way and provide comparable results.

Discussion

Models for investigating intra- and inter-variability in dyads are becoming increasingly important in the social and behavioral science. Researchers studying dyadic interactions are moving towards uncovering the dynamics that underlie the interrelations between the two individuals, as they unfold over time. Our approach in this paper is a step in that direction. We examined daily fluctuations of emotions among individuals in dyads using a mixed-effects location scale model. This technique was helpful to characterize such daily emotional ups and downs and their time-related signature as a function of individual and partner effects. Furthermore, it allowed us to obtain insights into the within-person variance, a component assumed to comprise what is left unexplained by the model. In our analyses, such residuals over time could be predicted by factors outside the dyad (e.g., weather), which permeated the daily ups and downs in affect.

Daily ups and downs in affect can also be modeled at the individual level using our approach. For example, models similar to the ones illustrated here could be used that include positive and negative affect separately for a given individual, with dummy code variables representing the type of affect rather than the dyad members, as in our case. This approach would allow a dynamic understanding of positive and negative together with the advantage of modeling the residual variance with covariates, as described here. Similarly, this logic could be extended to a larger set of variables (e.g., positive and negative affect for each dyad member) to model a dyadic multivariate dynamic process with covariates explaining the residual variances.

It is well known that patterns of variability can be systematic and reveal important information about the individual (e.g., Fox & Porges, 1985; Kagan, 1994; Nesselroade, 1991; Nesselroade & Boker, 1994). When an individual is part of a system (e.g., dyad), the patterns of variability in that person may be linked to those of the partner, potentially uncovering salient properties of the system. In this paper we show how residuals may contain similar important patterns that can be partitioned, explained, and used to better understand the dynamics of the interactions.

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Table 1

Parameter Estimates from a Mixed Effects Location Scale Model for Affect Ratio

	Female			Male		
Parameters	**Estimate**	**SE**	**t-v**	**Estimate**	**SE**	**t-v**
Fixed Location	.243		12.77			16.77
intercept β_{0t}	.259	.019	14.02	.292	.017	15.47
self affect β_{1t-1}	.359	.018	15.52	.265	.017	14.63
partner affect β_{2t}		.025		.329	.022	
Fixed Scale	−5.05		−480.9			−251.6
intercept τ_0	−.003	.011	−46.18	−4.93	.019	−33.01
weather τ_1		.001		−.007	.001	
Random Location	.033		40.71			13.85
intercept var. $\sigma^2{}_0$	.036	.001	38.16	.011	.001	27.66
self var. $\sigma^2\beta_1$	.080	.001	77.20	.028	.001	60.96
partner var. $\sigma^2\beta_2$	−.006	.001	−15.49	.065	.001	−10.67
cov. $\sigma_{0,1}$	−.041	.001	−99.87	−.005	.001	−81.20
cov. $\sigma_{0,2}$	−.028	.001	−48.78	−.035	.001	−33.85
cov. $\sigma_{1,2}$	−.002	.001	−3.80	−.021	.001	
cov. $\sigma_{0,0}$*	−.002	.001	−3.43			
cov. $\sigma_{1,1}$*	.006	.001	7.75			
cov. $\sigma_{1,1}$*		.001				
Random Scale	25.07		1.58			3.19
var. $\sigma^2\tau_0$	.052	18.9	17.80	15.16	4.74	12.01
var. $\sigma^2\tau_1$	5.96	.002	51.05	.065	.005	15.98
cov. $\sigma^2\tau_{0,1}$	.190	.117	0.07	1.55	.097	
cov. $\sigma^2\tau_{0,0}$*	−.005	2.60	−2.15			
cov. $\sigma^2\tau_{1,1}$*		.002				
Model Fit	48065					
−2LL	47896					
BIC						
	43 (10)					
$\chi^2(df)_{no\ scale}$						

Note. Number of dyads (N_d) = 165; Maximum number of daily observations per dyad (N_o) = 186; Total number of observations (N_T) = 20210; Number of unique parameters (N_p) = 33. Covariances denoted as "*" represent both individuals.

Table 2

Parameter Estimates from a Mixed Effects Location Scale Model for Positive Affect

	Female			Male		
Parameters	**Estimate**	**SE**	**t-v**	**Estimate**	**SE**	**t-v**
Fixed Location	1.124		13.40		.076	17.47
intercept β_{0t}	.293	.084	16.48	1.333	.017	18.96
self affect β_{1t-1}	.365	.018	16.36	.326	.019	15.59
partner affect β_{2t}		.022		.298		
Fixed Scale	−1.487		−120.0		.002	−78.49
intercept τ_0	−.001	.001	−30.78	−1.619	.001	−19.75
weather τ_1		.001		−.001		
Random Location	5.49		48.16		.110	28.05
intercept var. σ^2_0	.035	.114	7.82	3.09	.004	8.59
self var. $\sigma^2_{\beta 1}$	.046	.005	10.43	.031	.004	11.19
partner var. $\sigma^2_{\beta 2}$	−.030	.006	−1.95	.046	.013	−2.44
cov. $\sigma_{0,1}$	−.144	.016	−7.04	−.031	.001	−6.70
cov. $\sigma_{0,2}$	−.024	.020	−6.68	−.100	.001	−8.32
cov. $\sigma_{1,2}$	−.089	.004	−4.35	−.021		
cov. $\sigma_{0,0}$*	−.003	.021	−2.44			
cov. $\sigma_{1,1}$*	.008	.001	5.85			
cov. $\sigma_{1,1}$*		.001				
Random Scale	44.50		11.63		4.68	6.28
var. $\sigma^2\tau_0$	.001	3.83	12.79	29.38	.001	8.68
var. $\sigma^2\tau_1$	11.88	.001	45.70	.001	2.87	26.94
cov. $\sigma^2\tau_{0,1}$	.365	.2.56	.379	77.22		
cov. $\sigma^2\tau_{0,0}$*	.187	.963	7.19			
cov. $\sigma^2\tau_{1,1}$*		.026				
Model Fit	27896					
−2LL	28054					
BIC						
	1969 (10)					
$\chi^2(df)_{no\ scale}$						

Note. Number of dyads (N_d) = 165; Maximum number of daily observations per dyad (N_O) = 186; Total number of observations (N_T) = 20210; Number of unique parameters (N_p) = 33. Covariances denoted as "*" represent both individuals.